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# Multilevel Hypernetworks in the Design of Complex Multirobot Control Systems

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# Multilevel Hypernetworks in the Design of Complex Multirobot Control Systems

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***Abstract*-Increasingly engineering involves systems with many autonomous subsystems and agents. Understanding and controlling such systems is beyond the abilities of traditional control methods. The issues are well captured by the design and control of robot soccer systems. Hypernetworks generalize networks to relations between more than two items. They can be used to model multilevel relational structure, and it is shown how they can be applied to robot soccer systems. Some structural configurations are more disposed to good or bad outcomes than others, and these can be used in the control process. The theory is developed from first principles and illustrated by experiments performed in our laboratory.**

## I. Introduction

Increasingly engineering involves systems with many autonomous subsystems and agents. Conventional approaches to control do not apply at higher levels of abstraction, since these involve structural constructs at many levels of representation. The issues are well captured by the design and control of robot soccer systems, where two teams of robots compete to score goals against each other. This is a very attractive research platform because the objectives for the robot teams are easy to state and understand, because they span a very wide range of engineering sub-disciplines that have to be integrated, because the bring us face to face with the problem of engineering multilevel complex systems with autonomous components, and because it is easy to judge success and failure.

Representing the system and its dynamics in a coherent multilevel way is an essential requirement, involving both qualitative and quantitative dynamical relationships [1][2]. We propose the use of a new mathematic approach involving *hypernetworks* – a multilevel multidimensional generalisation of relational network theory [3].

The research has great potential for industrial applications since it addresses the generic problem of designing and controlling multilevel systems in which it is necessary to deal with combinatorially wide ranges of interactions that cannot all be foreseen by the system designer. The new mathematical approach demonstrated for robot soccer is equally applicable to the control of other complex multiagent systems.

## II. Multidimensional Representation

The game of football has a multidimensional structure. At the microlevel there are individual robots constructed from sub-microlevel components. The behaviour of the whole robot emerges from the dynamic properties of its parts and the way they are assembled. Usually conventional feedback control approaches work well at this level. At meso-level small groups of robots interact dynamically, creating spatial configurations that support capturing the ball, passing, and scoring goals. At the macro level, these dynamic groupings combine and disband, structuring the pitch through time according to strategies intended to be predisposed to good outcomes. To play the game requires a good understanding of some, if not all, of the relationships within this multilevel structure. Some relationships are global, existing in every game, such as those governed by the rules, whilst others may only appear in a single game or at a single moment, being a trait of a particular team, or tactic. Some typical factors in these multidimensional structures may be the position of players, velocity of the ball, kick-off events, pitch edges, fouls and game time.

Hypernetworks have been created to describe such complex structures. A hypernetwork represents structure between sets of nodes, a natural progression from a standard network representing structure between a pair of nodes. Whereas a network consists of agents related by lines, a 2-ary relation, a hypernetwork can consists of agents related by lines, triangles, or any other polyhedron, representing $n$-ary relations.

A polyhedron with $n$ vertices represents an $n$-ary relation and a polyhedron with ($p$+1) vertices is called a *p-simplex*. A set of simplices form a hypernetwork, with each simplex being associated with an edge of the hypergraph. Fig. 1 shows some simplices representing possible structures in football, whilst Fig. 2 shows hypernetworks of connected simplices.

Higher dimensional simplices can be decomposed sets of lower dimensional simplices, called their *faces*. If two simplices share a set of ($q$+1) nodes, then they will share a $q$-dimensional face, and are said to be *q-near*. Simplices sharing a single node are 0-near, while simplices sharing an edge are 1-near, and a triangle, 2-near (Fig. 2).

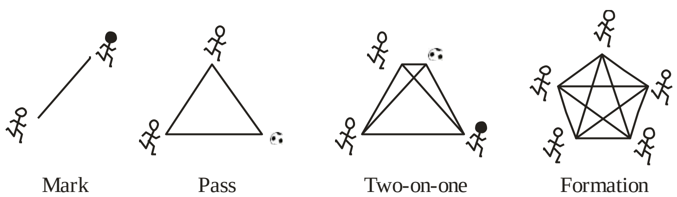



Fig. 1. Simplices of events in football. 'Mark' is a 1-simplex, having 2 vertices, whereas 'Formation' is a 4-simplex.

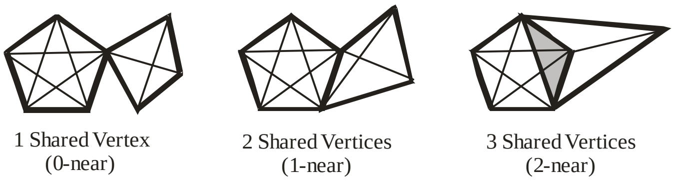
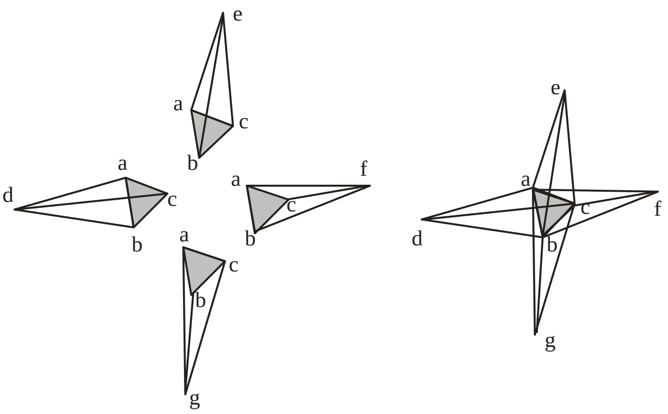



Fig. 2. Hypernetworks of q-near simplices. Simplices sharing a single node are 0-near, while simplices sharing an edge are 1-near, and a triangle, 2-near.

The connectivity described above is based on shared faces of pairs of simplices. This can be extended to considering shared faces between many simplices. Fig. 3 shows four simplices ‹ *a*, *b*, *c*, *d* ›, ‹ *a*, *b*, *c*, *e* ›, ‹ *a*, *b*, *c*, *f* ›, and ‹ *a*, *b*, *c*, *g* ›, which all share the face ‹ *a*, *b*, *c* ›. This set of simplices is called a *star*, and the largest shared face is referred to as the *hub*. In this way, a hub signifies a strong correlation between the simplices. The more vertices contained in the hub, the stronger the link between simplices. Similarly, the more simplices forming a star, the more relevant the hub becomes in classifying those simplices. Therefore, hubs and stars can be used to identify strong links between sets of data.

The connectivity of a hypernetwork can be partially tabulated using an incidence matrix (Table I). By rearranging the rows and columns of this matrix, connected vertices can be grouped into blocks, or *maximal rectangles*, which correspond to the hubs of the hypernetwork. The *rectangle number* is the area of the maximal rectangle; the larger the rectangle, the closer the correlation between simplices [4].



(a) Simplices with shared faces

(b) Star of the simplices showing the common hub

Fig. 3. A star-hub configuration. The more vertices contained in the hub, the stronger the link between simplices.

TABLE I
INCIDENCE MATRIX FOR FIG. 3

| Simplex | Vertices | | | | | | |
|---|---|---|---|---|---|---|---|
| | a | b | c | d | e | f | g |
| 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 2 | 1 | 1 | 1 | 0 | 1 | 0 | 0 |
| 3 | 1 | 1 | 1 | 0 | 0 | 1 | 0 |
| 4 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |

= Maximal rectangle

## III. Multilevel Structure

As well as having multidimensional structure, robot football is multilevel; it contains an inherent hierarchy.

In Fig. 1 names are attributed to the simplices to signifying what they represent. The simplex maps the set of nodes at one level to the named structure, which is a higher level of representation (Fig. 4). These named structures are themselves elements in even higher level structures.

The relationship described by the simplex is crucial. A set of elements configured in two distinct ways can have completely different meanings. Consider the sets shown in Fig. 5. Both show three players and a ball, $\{w_1, w_2, b_1, B\}$, though each has a different relationship, denoted $R_1$ and $R_2$. The relationship $R_1$ gives rise to the significant structure named *defenders dilemma*, whereas $R_2$ gives a separate configuration, which has no significant meaning, and has not been named. The notation $\langle w_1, w_2, b_1, B; R_i \rangle$ is used to represent the structure created by imposing the relation $R_i$ on the set of elements $\{w_1, w_2, b_1, B\}$.

The conical structure shown in Fig. 4 represents the *Fundamental Diagram of Multilevel Systems*. The base of the cone represents a particular set of variables, whilst the sides of the cone represent a relation, which maps the set to a particular structure at the apex. If the set of variables lies at level *N* within the hierarchy, the structure described by the relation lies at level *N+1*. In this way, the multilevel structure is closely linked to the idea of *emergence*; by applying a relation to a set of unstructured variables at level *N*, a structure emerges at level *N+1*.

Fig. 6 shows a possible multilevel representation of a role-based robot football architecture. It depicts 3 distinct levels of

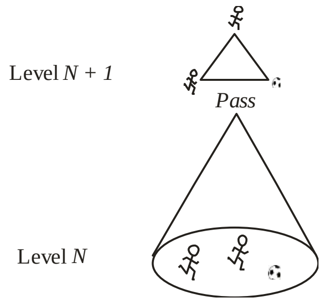



Fig. 4. A hierarchical mapping of elements into named structures.

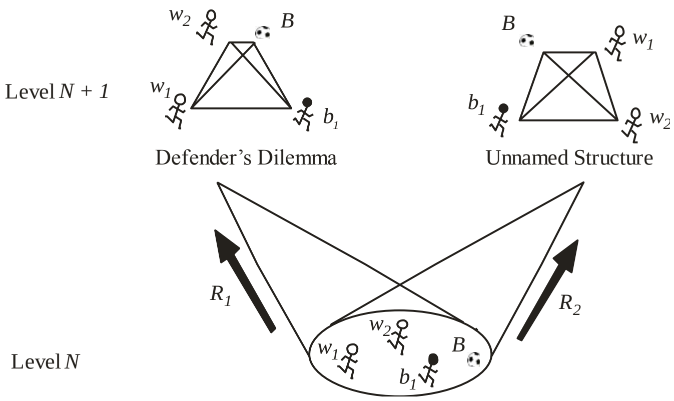



Fig. 5. A set of elements mapped into two distinct structures.

uses a hypothesis test introduced in [2]:

Variables, primitives and concepts can be graphically represented using hypernetworks: Each variable is drawn as a vertex, joined by a structure representing the relation between them. This structure of variables forms the primitive at level *N*, which can then be mapped onto the named concept, which appears at level *N+1*, as shown in Fig. 4. Since the simplex is a relational structure between variables, the attached concept is relational rather than general.

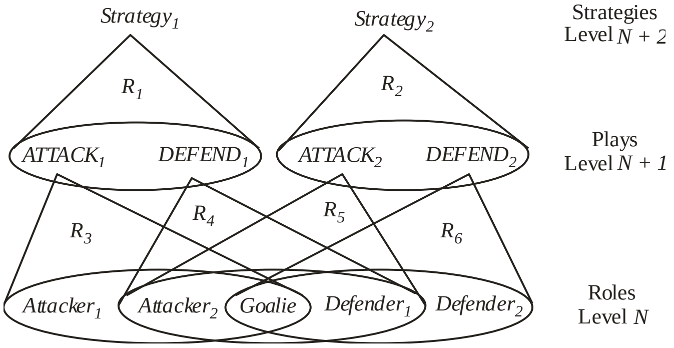



Fig. 6. A possible robot football hierarchy.

hierarchy, with linking relationships. It can be seen that bases of cones can fully or partially overlap, but that when mapped by different relationships give rise to separate structures.

## IV. Concept Generation

This paper uses the method of concept generation [5] to abstract simplices from sets of arbitrarily chosen variables.

A *concept* is a generalisation of a set of *primitives* bound together by a *hypothesis*. If the primitives are similar features in a football match, the hypothesis describes the common structures in each. For example, if the primitives are three different pass situations, a relational hypothesis will exist which can be used to group them into the concept *PASS*.

There are two distinct varieties of concept. *Generalisation concepts* represent a class of primitives. For example, three different ball passes in football can all be generalised to the concept *PASS*. A single pass is sufficient to be classed as an example of the concept. The second concept is called a *relational concept*; relating a set of distinct primitives via some structure. In this case, the concept *PASS* could be made up of a ball, a passing player, and a receiving player, in a certain configuration. In this example all three primitives, and the structure, are required to generate the concept.

Primitives are described by a set of *properties* or *variables*, which can be values or measurable definitions. Fig. 7 shows the relation between variables, primitives, hypotheses, and concepts. Here, shape, size, colour and weight are the variables. The primitives are plum, marble, melon, doll, domino, and orange. Fruit and toy are the two concepts into which the primitives are grouped by the hypothesis.

The hypothesis can be represented in many ways. This paper

| Primitive | Variable | | | |
|---|---|---|---|---|
| | Shape | Size | Colour | Weight |
| Plum | Spherical | Small | Purple | Light |
| Marble | Spherical | Small | White | Light |
| Melon | Spherical | Large | Yellow | Heavy |
| Doll | Irregular | Large | Pink | Light |
| Domino | Cuboid | Small | Black | Light |
| Orange | Spherical | Medium | Orange | Medium |

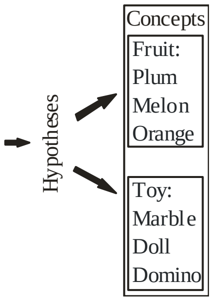



Fig. 7. A hypothesis classifies primitives into associated concepts by identifying patterns in sets of variables.

Consider a group of primitives which relate to a single concept. Each primitive will form its own simplex. If the primitives can be related through their variables, the set of simplices will overlap to form a star. The hub of this star gives a possible hypothesis for relating the primitives to the concept. For example, in Fig. 3, the simplices all represent some concept and share the face ‹ *a*, *b*, *c* ›. The generated hypothesis will be that any primitive containing the structure ‹ *a*, *b*, *c* › will also be a member of the same concept. A hub used to define a concept in this way is called a *classifier hub*.

If a set of simplices do not share a hub, then the attached primitives are members of separate concepts. Similarly, if stars form more than one hub, then the primitives involved are members of more than one concept.

This method of analysis has previously been demonstrated in [5] for classifying plant types from sepal and petal dimensions. Hubs were generated using a training set of 75 samples, relating to 3 plant types. 150 samples were then categorised using a single classifier hub for each type of plant. The technique correctly classified 86% of samples, with 30% unclassified, and none misclassified. To verify the significance, two neural networks were constructed; one using all 40 plant variables, and the other using only the 14 variables used in the 3 classifier hubs. Both networks displayed similar accuracies when used to reclassify the plant data.

For concepts to be used as behaviours in a set of robots, they must be assigned *representatives*. These are representations of the concept, which can be sent as commands to the robot. Depending on the level, these representatives may simply be one of the primitives used to define the concept, a combination of the primitives, or some kind of approximation or average of the primitives. The hub of a set of simplices forming a concept is commonly used as the representative.

## V. Structure in Robot Football

Robot football (or soccer) was devised in [6], and gained popularity through the RoboCup initiative [7]. It is the focus of a large and successful research community and, following the climax of Deep Blue beating Gary Kasparov at chess in 1997 [8], has been proposed as the new benchmark challenge for Artificial Intelligence [9].

In essence similar to human football, robot football is a game played by two teams of simulated or physical robot agents on a rectangular pitch, whereby the aim is to transfer a ball into the opposing team's goal area. Many different leagues exist, each played in competition at international level, with research institutions battling it out to show their systems are the most advanced. These leagues range from one-on-one humanoid games, through large, distributed, 5-a-side wheeled teams, to small, fast, centralised, 11-a-side robot games, and simulated games.

Fig. 6 showed a typical strategy structure using a *role* based approach. This is a common approach wherein team strategies are divided into plays, each containing a set of predefined robot roles. These roles contain low level information about the actions of each robot, such as positioning, movement, area boundaries, passing and shooting. They are usually based on functional concepts relating to human football, such as goalkeeper, defender, or striker. This approach is limited by the creativity of the programmer, and is not suited to larger team sizes.

An alternative, for such a complex system, is to use learning techniques. These fall into two categories: In systems such as [10] and [11], the focus is on learning individual skills or game aspects using reinforcement methods, which are compiled into a complete strategy. These use a variety of learning algorithms to build behaviours from the ground up are development intensive, requiring many different skills to be identified and learnt using separate techniques. Alternatively, entire strategies can be formed in one operation using evolutionary techniques, as in [12]. These emergent strategies do not contain enough information to be competitive, often evolving to ball-crowding strategies.

The approach described here is a new method which aims to reconstruct the complexity of a football strategy by observing and mimicking structures in existing teams. The advantage is that the same technique can be used to learn behaviours at every level in the strategy structure.

It was shown, in [13], that the areas controlled by players, and hence the structures between them, are significant dimensions of the game. Furthermore, [14] showed a number of specific player configurations which had significant meanings. Based on these initial findings, hypernetworks can be used to map these structures to a representation of the game of football. The approach, described below, is based on analyzing structures between the players, ball and features on the pitch, and identifying those which occur more frequently in successful teams.

## VI. Strategy Abstraction

Initially, a structural representation of the system must be formed. In this work, the structure is generated by hand from knowledge of the system. Fig. 8 shows an example of a possible structure for robot football based on observation. If the structure is an accurate representation of the system, then by carefully constructing each element, it should be possible to create a working system.

Each element in the structure is a named concept, and is composed of a set of variables. In this paper we focus on the strategy and play level concepts in order to generate a formational controller. The more levels and concepts inserted

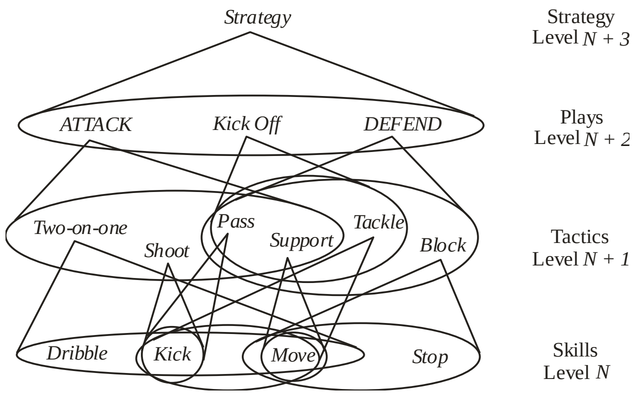



Fig. 8. A multilevel strategy structure consisting of a hierarchy of skills tactics and plays.

into the hierarchy (provided they are well chosen), the more accurate the football representation will become. However, since our robots currently lack the abilities required for ball handling, we shall focus on recreating the formational structures of football identified in [14], which occur at the higher levels.

The next stage is to generate a list of variables which will be used to describe the primitives and concept. The results described here were obtained by measuring 66 arbitrarily chosen variables. These are not described here to save space, but range from the frequency of occurrence of events, such as passes, to spatial relationships, such as distance between neighbouring players. Some of the variables are themselves concepts identified at a lower level in the hierarchy.

A set of primitives are measured from recordings of previous football matches. These are the values of the variables taken over the duration of the concept. In the case of the strategy concept variables are measured over the entire duration of a match.

Primitives are classified as *desirable*, *undesirable*, or *indifferent* depending on how they relate to the concept. A combination is used to construct the hypothesis. For example, strategy primitives which result in a win are classed as desirable, a loss as undesirable, and a draw as indifferent. By distinguishing between variables in the desirable and undesirable sets, we find the structures that influence whether a strategy wins or loses.

Three averages are generated for each variable: average over all primitives, average over desirable primitives, and average over undesirable primitives. These averages are compared to determine whether the variable is included in the hypothesis for the related concept. An example, based on real data, is shown in Fig. 10.

If the average values for a variable recorded for the desirable and undesirable primitives are on opposite sides of the global average, then it is a possible classifier for differentiating between the two types of primitive. If the two averages fall on the same side of the global mean, made possible by the inclusion of indifferent primitives, then the variable is not a classifier. Variables for which the difference between averages

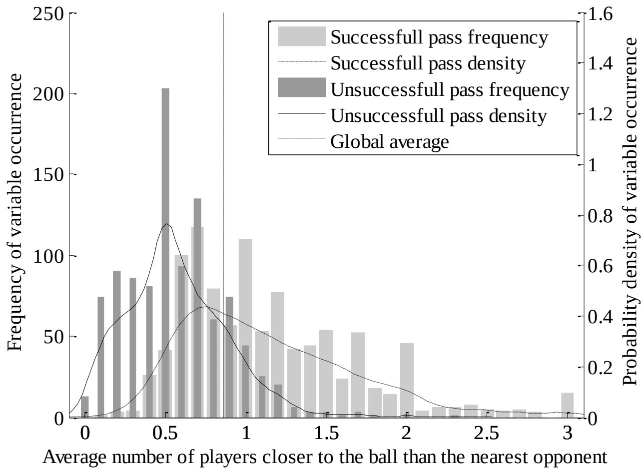



Fig. 10. Classification of variables by average. In this example, the variable is used to differentiate between successful and unsuccessful passes. Out of 2036 passes, it correctly classifies 629 successful passes, and misclassifies 161 unsuccessful passes.

is less than a threshold (here 5% of the entire range) are common to both. In terms of a football strategy primitive, the classifier variables can provide information on how to play well, or play badly, whilst the common variables provide information relating to the fundamental requirements of the game.

An incidence matrix of desirable primitives and classifier variables is generated. Each entry is valued '1' if the variable occurs in the primitive on the on the same side of the global average as the desirable average.

The final stage of the process is to perform the star-hub analysis on the data in the incidence matrix. Each primitive forms a star, with the hubs of those stars being common structures between primitives. These common structures can be used as hypotheses linking a set of variables to a concept, and therefore identify significant structures. If a hub of *dimension* $n$ is a hub containing $n + 1$ vertices, then a hub of $m + 1$ intersecting simplices is an *intersection* of dimension $m$. Generally hubs with large $m$ will have small $n$, and vice-versa.

## VII. RESULTS

This analysis was performed on data from ten matches undertaken in the RoboCup Simulation League. The 66 variables were measured from the perspective of each team giving 20 strategy primitives, 20 attacking play primitives, and 20 defending play primitives. Strategy primitives were measured over the entire match from the perspective of one team, whereas attacking and defending primitives focused respectively on frames with the ball in the away or home half of the pitch. These were split into 8 desirable, 4 indifferent and 8 undesirable sets by goal difference; primitives relating to teams winning a match generating desirable primitives, and games resulting in a draw generating indifferent primitives. It should be noted, however, that there may be other acceptable criteria by which to rate the primitives. For example, it may be more appropriate to rate defending primitives in terms of a goal being conceded, or the ball being played into the opponents half, which would give a slightly different set of results.

Performing the analysis on each set of primitives generates sets of hubs relating to each of our strategy and play concepts. For the strategy concept, for example, we find that 34 of the variables occur with a higher probability in winning teams, and that these form 91 unique maximal hubs (The algorithms used only record the largest dimension of hub joining a set of simplices. Sub-sets occurring with the same frequency are ignored). For each dimension of intersection Table II shows the largest hub which covers that many primitives. There is no hub which occurs across all 8 winning primitives.

Variable $x_{17}$, which appears in 7 of the 8 strategies, relates to the percentage of shots on the opponent goal which are successful. The analysis shows that in winning teams $x_{17} > 31.09$. This seems logical, since it relates directly to the score of each team. In the only winning primitive, $p_7$, where $x_{17} < 31.09$, 10 shots were taken, with only 2 being successful. In this case, the high number of attempts was sufficient to score a win. Variable $x_6$ also occurs in 7 of the 8 winning strategies with a value of $< 49.58$, and is the most common variable, occurring in 58 of the 91 hubs. This is the percentage of time the ball spends in the home players half, and indicates that these winning strategies spend more time on the offensive, which is a sensible assumption. Conversely, variable $x_{59} > 0.01$ only appears in 2 of the winning strategies. This represents the average number of instances per frame that 4 home players team up to mark an opponent player. This is obviously a rare occurrence, but its predominance in winning teams suggests it could be a useful tactic in some situations. Of course, it is not the occurrence of the variables on their own that is of interest, but their occurrence in the emergent combinations.

The relationship $R$ is the same for every hub. In this case, it represents each variable occurring with an appropriate average value over the duration of the match. 8 variables were identified as being common to both winning and losing teams, and are added to these hubs as they represent structures fundamental to the game of football.

From each of the three lists of hubs, we select the largest and most frequently occurring which contain data on spatial structures to be representatives for the concepts. These are

TABLE II
MAXIMAL STRATEGY HUBS

| Dimension of intersection | Maximum hub dimension | Largest hub |
|---|---|---|
| 6 | 0 | $\langle x_{17} ; R \rangle$ |
| 5 | 5 | $\langle x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30} ; R \rangle$ |
| 4 | 11 | $\langle x_{10}, x_{13}, x_{15}, x_{21}, x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32} ; R \rangle$ |
| 3 | 15 | $\langle x_6, x_7, x_{10}, x_{13}, x_{15}, x_{21}, x_{23}, x_{24}, x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32} ; R \rangle$ |
| 2 | 20 | $\langle x_5, x_6, x_7, x_8, x_9, x_{10}, x_{13}, x_{15}, x_{17}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32} ; R \rangle$ |
| 1 | 23 | $\langle x_3, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{15}, x_{17}, x_{18}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32} ; R \rangle$ |
| 0 | 27 | $\langle x_3, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{15}, x_{16}, x_{17}, x_{18}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{26}, x_{27}, x_{28}, x_{29}, x_{30}, x_{31}, x_{32}, x_{41}, x_{44} ; R \rangle$ |

combined to define five multilevel football strategies consisting of formational plays.

These strategies are fed into a controller which attempts to reproduce the variables in the representatives. At each frame, the controller selects the appropriate representative, and creates a model of the football pitch in terms of the desired variables. For our spatial variables, this entails creating a map of the pitch divided into segments representing those spaces. The controller then searches the spaces for the set of robot positions which will most closely recreate the values of the variables in the representative.

In initial tests, the controller is used to create target positions in response ball and opponent positions in 1000 randomly selected frames of recorded robot football data. It identifies targets which successfully recreate the representative with a rate of 71-100% over the five strategies. In terms of the individual variables, the success rate is 94-100%.

The controller was implemented on a set of Mirosot football robots against a traditionally programmed strategy. A section of the resulting match is shown in Fig. 11 which shows how the area controlled by the team appears connected to the position of the ball. This conforms with our results in [14] which show that the area controlled by a football team is related to the position of the ball. Importantly, this behaviour is not programmed, but emerges from the interactions of the variables composing the abstracted representatives.

## VIII. Conclusions

The problem of controlling multilevel multiagent robot systems has been addressed using concepts from the mathematical theory of hypernetworks. This has been illustrated by a number of examples taken from real soccer games played with real robots described in [15]. The main idea developed in this paper is that agents such as robots and the ball can be combined under *n*-ary relations to form structure at higher levels. In turn these can be combined to form high level structures, to give greater degrees of abstraction. It is these *discrete* aspects of the system that are used when reasoning at tactical and strategic levels. In neural systems they can correspond to the discrete event of a neuron firing, when some particular structure has been recognised.

The hypernetwork approach discussed has great generality, having been devised over many years for the analysis, management and control of complex social, socio-technical and engineered systems [16]. It can be argued that multirobot robot systems form an intermediate class of complex systems, between physical systems in which the agents (*e.g.* atoms, molecules, rocks, air streams) do not play a sentient role in the system dynamics and their governing laws, and social systems in which human can change the meta-rules that create environments for the emergence of social structures and their dynamics. Thus multirobot systems such as robot soccer not only provide an excellent platform for research into robotics and multiagent systems, they also have the potential to play a strategic role in developing the more general science of complex systems.

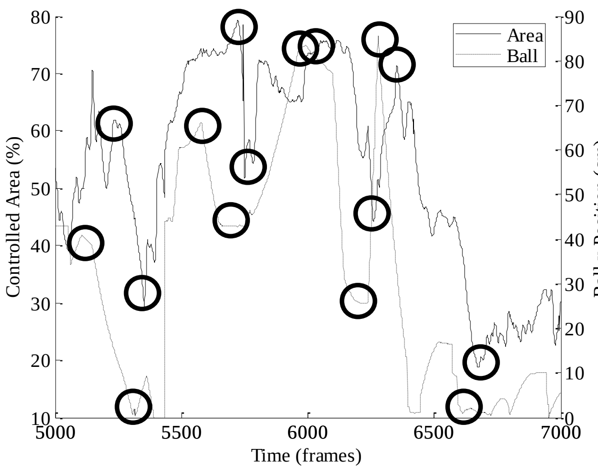


Fig. 11. Comparison of ball position and controlled team area highlighting similar features.

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